Measuring Informational Distances Between Sensors and Sensor Integration

Lars Olsson*, Chrystopher L. Nehaniv*† and Daniel Polani*†
Adaptive Systems* and Algorithms† Research Groups
School of Computer Science, University of Hertfordshire
United Kingdom
{L.A.Olsson, C.L.Nehaniv, D.Polani}@herts.ac.uk

Abstract

In embodied artificial intelligence is it of interest to study the informational relationships between the agent, its actions, and the environment. This paper presents a number of statistical measures to compute the informational distance between sensors including the information metric, correlation coefficient, Hellinger distance, Kullback-Leibler, and Jensen-Shannon divergence. The methods are compared using the sensory reconstruction method to find spatial positions of visual sensors of different modalities in a sensor integration task. The results show how the information metric can find relations not found by the other measures.

Introduction

In the early 1960s H. B. Barlow suggested (Barlow, 1961) that the visual system of animals "knows" about the structure of natural signals and uses this knowledge to represent visual signals. Ever since then neuroscientists have analysed the informational relationships between organisms and their environment. In recent years, with the advent of embodied artifical intelligence, there has also been an increased interest in robotics and artificial intelligence to study the informational relations between the agent, its environment, and how the actions of the agent affect its sensory input. It is believed that this research can give us new principles and quantitative measures which can be used to build robots that can exploit bootstrapping (Prince et al., 2005) and continously learn, develop, and adapt depending on their particular environment, environment, and task to perform. This paper presents some work in this area and presents a number of methods for computing the distance between sensors and how these methods can be useful for sensor integration of different sensor modalities.

The informational relationships between sensors are dependent on the particular embodiment of an agent. Thus, these relationships can be useful for the agent to learn about its own body, the potential actions it can perform, and how the sensors relate to its particular environment. In (Olsson et al., 2004b) the sensory reconstruction method, first described by Pierce and Kuipers (1997), was applied to robots and extended by considering the informational relations between sensors. The results showed how the visual field could be reconstructed from raw and uninterpreted sensor data and how some symmetry of the physical body of the robot could be found in the created sensoritopic maps. This method was also used in (Olsson et al., 2005b) to show how a robot can develop from no knowledge of its sensors and actuators to perform visually guided movement.

One other aspect of the information available in an agent's sensors is that the particular actions of the agent can have an impact on the nature and statistical structure of its sensoric input. This has been studied in a number of papers since (Lungarella and Pfeifer, 2001); see for example (Sporns and Pegors, 2003, 2004; Lungarella et al., 2005). The results show how saliency guided movement decreases the entropy of the input while increasing the statistical dependencies between the sensors. The specific environment of an agent also limits in principle what an agent can know about the world and the physical and informational relationships of its sensors (Olsson et al., 2004a).

Information-theoretic measures have also been used to classify behaviour and interactions with the environment using raw and uninterpreted sensor data from the agent. In (Tarapore et al., 2004) the statistical structure of the sensoric input was used to fingerprint interactions and environments. Mirza et al. (2005b) considered how the informational relationships between its sensors, as well as actuators, can be used to build histories of interaction by classifying trajectories in the sensorimotor phase space. In (Kaplan and Hafner, 2005) the authors also considered clustering behaviours by the informational distances between sensors by considering configurations of matrices of information distances between all pairs of sensors.

One important issue in this research is what measures to use to quantify the informational relationships. In (Lungarella et al., 2005) the authors present a number of methods for quantifying informational structure in sensor and motor data. The focus is on integration, i.e., how much information two or more sources have in common. In this paper we focus on the opposite, i.e., how to compute how different two or more sources are. Following (Olsson et al., 2004b), several papers including (Olsson et al., 2004a, 2005b,c,a, 2006; Mirza et al., 2005a,b; Kaplan and Hafner, 2005; Hafner and Kaplan, 2005) have used the information distance metric disucssed by Crutchfield (1990) to compute the informational distance between sensors. An important question the authors have received several times in reviews of papers and in discussions is "why the information metric?". This is a good question and in this paper we present a number of alternative distance measures suggested by colleagues and reviewers as well as the information metric. To compare the potential utility of the methods we apply them as the distance measure used in the sensory reconstruction method (Pierce and Kuipers, 1997; Olsson et al., 2004b). In the experiment the sensors of the visual field of a robot is split into three different modalities: red, blue, and green, and the problem is to find the relationships between sensors, including which sensors come from the same pixel in the camera. This is an example of sensor integration. The results show how the information metric performs better in this problem as it measures both linear as well as non-linear relationships between sensors.

The rest of this paper is structured as follows. The next section presents a number of methods to compute the distance between two sensors. Then a short introduction to the sensory reconstruction method is given before the results of the experiments are presented. The final section concludes the paper.

Measuring the Distance Between Sensors

In this section we present a number of methods for computing the distance between two sensors S_x and S_y. Each sensor can assume one of a discrete number of values (continuous values are discretized) $S_x^t \in \mathcal{X}$ at each time step t where $\mathcal{X}$ is the alphabet of possible values. Thus, each sensor can be viewed as a time series of data $\{S_x^1, S_x^2, \ldots, S_x^T\}$ with T elements. Each sensor can also be viewed as a random variable X drawn from a particular probability distribution $p_x(x)$, where $p_x(x)$ is estimated from the time series of data. Similarly the joint probability distribution $p_{x,y}(x,y)$ is estimated from the sensors S_x and S_y.

A distance measure $d(X,Y)$ is a distance function on a set of points, mapping pairs of points (X,Y) to non-negative real numbers. A *distance metric* in the mathematical sense also needs to satisfy the three following properties:

- $d(X,Y) = d(Y,X)$ (Symmetry).
- $d(X,Y) = 0 \quad \text{iff} \quad Y = X$ (Equivalence).
- $d(X,Z) \leq d(X,Y) + d(Y,Z)$. (Triangle Inequality).

If (2) fails but (1) and (3) hold, then we have a pseudometric, from which one canonically obtains a metric by identifying points at distance zero from each other. This is done here and in (Crutchfield, 1990).

Why can it be useful to use distance measures which are metrics in the mathematical sense? If a space of information sources has a metric, is it possible to use some of the tools and terminology of geometry. It might also be useful to be able to talk about sensors in terms of spatial relationships. This might be of special importance if the computations are used to actually discover some physical structure or spatial relationships of the sensors, for example as in (Olsson et al., 2004b), where the spatial layout of visual sensors as well as some physical symmetry of a robot was found by information theoretic means.

Distance Measures

The *1-norm distance* used in (Pierce and Kuipers, 1997) is different from the distance measures that follows in that it does not take in to account the probabilites of the different values that a sensor can take. It is normalized between 0.0 and 1.0 and is defined as

$$d_1(S_x, S_y) = \frac{1}{T} \sum_{t=1}^{T} |S_x^t - S_y^t|. \tag{1}$$

The *correlation coefficient* is defined as

$$r = \frac{\sum_{t=1}^{T} (S_x^t - \bar{S_x})(S_y^t - \bar{S_y})}{\sqrt{\sum_{t=1}^{T} (S_x^t - \bar{S_x})^2} \sqrt{\sum_{t=1}^{T} (S_y^t - \bar{S_y})^2}} \tag{2}$$

where $\bar{S_x}$ and $\bar{S_y}$ are the mean of S_x and S_y respectively. The range of r is $-1.0 \leq r \leq 1.0$, where 1.0 means that they are perfectly correlated in a linear way, 0 that they are not linearly correlated, and -1.0 perfectly negatively correlated. This can be made symmetric by computing the squared correlation coefficient, which is in the range $0 \leq r^2 \leq 1.0$, and then

$$d_{CC}(S_x, S_y) = 1 - r^2_{S_x,S_y}. \tag{3}$$

This is still not a metric since it does not satisfy the triangle inequality (Ernst et al., 2005).

The *information metric* is proved to be a metric in (Crutchfield, 1990) and is defined as the sum of two conditional entropies, or formally

$$d_{IM}(S_x, S_y) = H(X|Y) + H(Y|X), \tag{4}$$

where

$$H(Y|X) = -\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(x,y) \log_2 p(y|x). \tag{5}$$

The *Kullback-Leibler divergence* (Cover and Thomas, 1991) is defined as

$$D(p_x || p_y) = \sum_{x \in \mathcal{X}} p_x(x) \log_2 \frac{p_x(x)}{p_y(x)}, \tag{6}$$

where $0 \log_2 \frac{0}{p_y} = 0$ and $p_x \ \log_2 \frac{p_x}{0} = \infty$. The Kullback-Leibler measure is not a metric because it is not symmetric. It can be made symmetric by adding two Kullback-Leibler measures,

$$d_{KL}(S_x, S_y) = D(p_x||p_y) + D(p_y||p_x), \tag{7}$$

where p_x is the probability distribution associated with sensor S_x and p_y with S_y. This is still not a metric since it does not satisfy the triangle inequality.

The square root of the *Hellinger distance*, also known as *Bhattacharya distance* (Basu et al., 1997) , is a metric and is defined as

$$d_H(S_x, S_y) = \sqrt{\frac{1}{2} \sum_{x \in X} \left(\sqrt{p_x(x)} - \sqrt{p_y(x)} \right)^2}. \tag{8}$$

Finally, the *Jensen-Shannon divergence*, presented in (Lin, 1991), is defined as

$$d_{JS}(S_x, S_y) = H(\pi_X X + \pi_Y Y) - \pi_X H(X) - \pi_Y H(Y), \tag{9}$$

where $\pi_X, \pi_Y \leq 0, \pi_X + \pi_Y = 1$, are the weights associated with the sensors S_x and S_y. In this paper the weights were always $\pi_X = \pi_Y = 0.5$. In (Endres and Schindelin, 2003) it was proved that the Jensen-Shannon is the square of a metric, i.e., $\sqrt{d_{JS}}$ is a metric, which was used in the experiments presented in this paper.

Sensory Reconstruction Method

In the sensory reconstruction method (Pierce and Kuipers, 1997; Olsson et al., 2004b) sensoritopic maps are created that show the informational relationships between sensors, where sensors that are informationally related are close to each other in the maps. The sensoritopic maps might also reflect the real physical relations and positions of sensors. For example, if each pixel of a camera is considered a sensor, is it possible to reconstruct the organization of these sensors even though nothing about their positions is known. It is important to note that using only the sensory reconstruction method, only the positional relations between sensors can be found, and not the real physical orientation of the visual layout. To do this requires higher level feature processing and world knowledge or knowledge about the movement of the agent (Olsson et al., 2004b). Figure 1 shows an example of a sensoritopic map for a SONY AIBO robot.

To create a sensoritopic map the value for each sensor at each time step is saved, where in this paper each sensor is a specific pixel in an image captured by the robot. The first step of the method is to compute the distances between each pair of sensors. In the paper by Pierce and Kuipers (1997) the 1-norm distance was used but after (Olsson et al., 2004b) the information metric has been used in a number of papers. In this paper the different distance measures presented

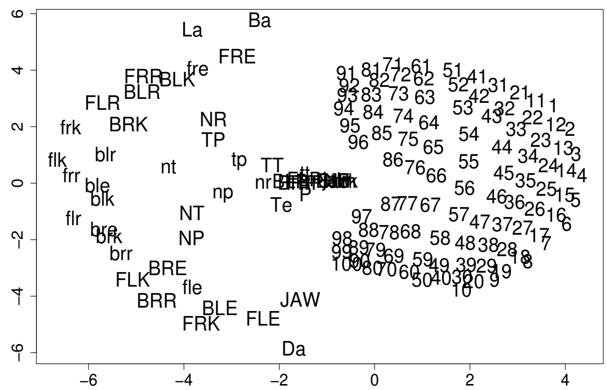


Figure 1: A sensoritopic map created by the sensory reconstruction method taken from (Olsson et al., 2004b) using the information metric. In this example there are 150 sensors, including 100 image sensors that are labeled 1-100 to the right in the map.

in the previous section are used. From the matrix of pairwise distance measurements between the sensors the dimensionality of sensory data (two in this case of a visual field) is computed and a sensoritopic map of that dimensionality can be created, using a number of different methods such as metric-scaling, which positions the sensors in the two dimensions of the metric projection. In our experiments we have used the relaxation algorithm described by Pierce and Kuipers (1997).

Experiment

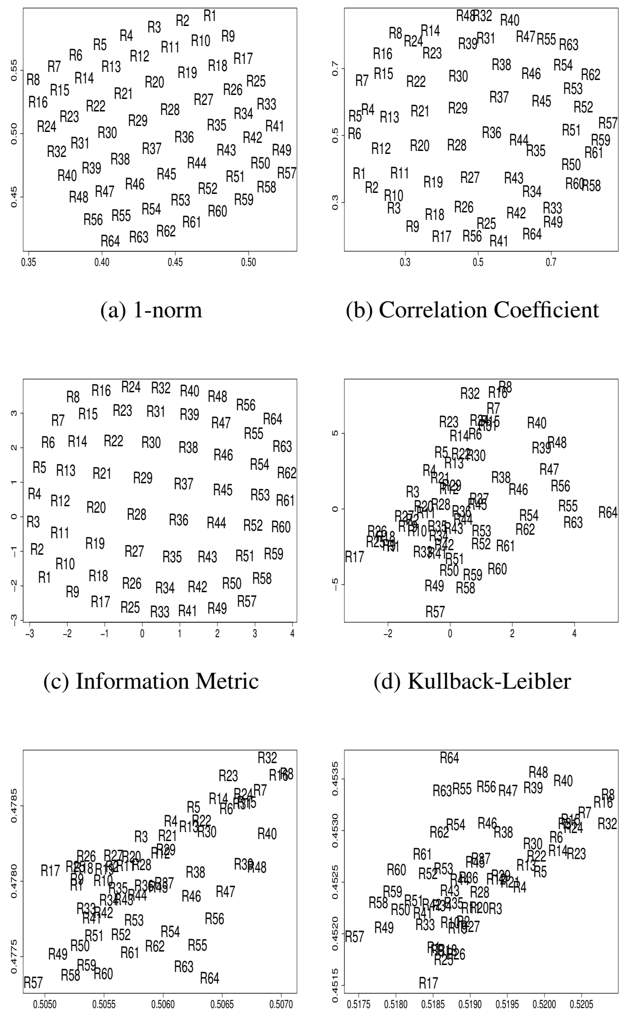
This section describes the performed experiment and the results.

Method

In our experiments a SONY AIBO robotic dog was placed in a sitting position on a desk in the lab. The robot only moved its head with uniform speed using the pan and tilt motors in eight directions: up, down, left, right, and four diagonal directions. Five sequences of 6000 frames each of visual data was collected from the camera at a resolution of 88 by 72 pixels with 8 bits for each channel (red, green, blue) at an average rate of 20 frames per second. The collected images were downsampled to 8 by 8 pixels using averaging. Each pixel of the image had one red, one green, and one blue sensor. Thus, there is a total of 192 sensors (64 of each modality) where the red sensors are labeled $R1 - R64$, the green $G1 - G64$, and the blue sensors $B1 - B64$. The sensors labeled 1 are located at the upper left corner of the image and 64 at lower right corner. In the collected data the range of

Measure \ Exp.	64R	192RGB	192ARGB
1-norm	0.06 (0.01)	0.32 (0.01)	–
Correlation coefficient	0.19 (0.02)	0.23 (0.03)	0.21 (0.05)
Information metric	0.07 (0.02)	0.12 (0.03)	0.09 (0.03)
Kullback-Leibler	0.37 (0.03)	0.35 (0.01)	0.41 (0.05)
Hellinger	(0.45 (0.05)	0.40 (0.02)	0.46 (0.04)
Jensen-Shannon	0.45 (0.04)	0.39 (0.01)	0.45 (0.04)

Table 1: Average distances between all pairs of correct and reconstructed sensors using equation 10 with standard deviation in parentheses. The column 64R shows the average distances for the 64 red sensors of figure 2 and 192RGB the red, green, and blue sensors of figure 3, both using normal binning. 192ARGB shows the results for the adaptive binning of figure 4.



(a) 1-norm (b) Correlation Coefficient

(c) Information Metric (d) Kullback-Leibler

(e) Hellinger (f) Jensen-Shannon

Figure 2: Sensoritopic maps of the red sensors.

the blue sensors was slightly lower than the red and green sensors with a slightly smaller variation.

Sensoritopic maps were created from each of the five sequences of data by the sensory reconstruction method using the different distance measures previously described. The presented maps are examples but all maps created using one particular distance measure had the same characteristics as the ones presented here.

Results

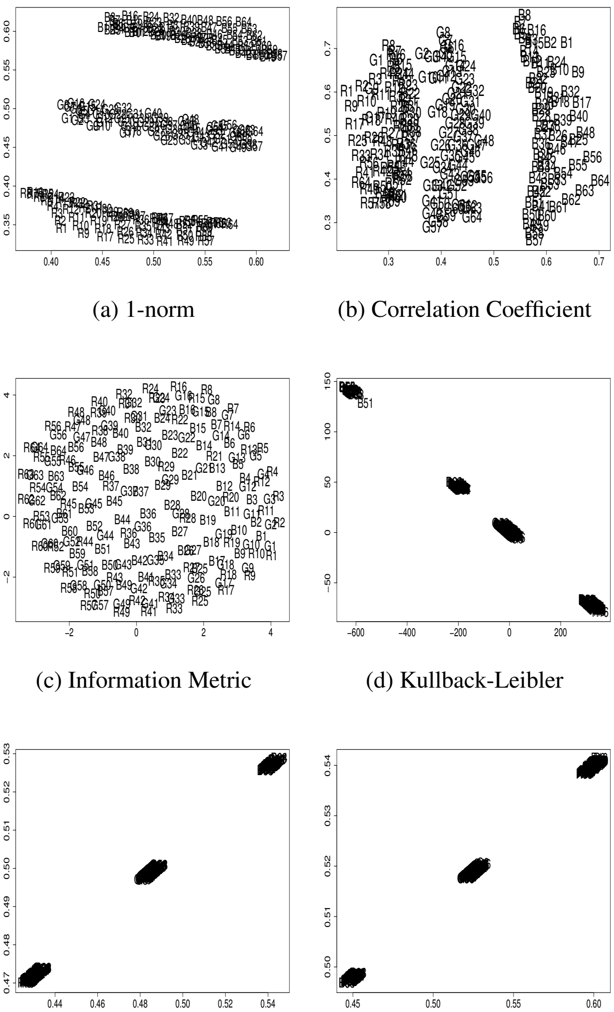
Figure 2 shows sensoritopic maps computed with the different distance measures of only the red sensors $R1-R64$. First, if we look at the maps for the Kullback-Leibler, Hellinger, and Jensen-Shannon distance, we find no real structure. For the correlation coefficient distance, figure 2(b), we find that sensors that are close in the visual field tend to be closer in the sensoritopic map, but it is not very clear. Now, compare this to the sensoritopic maps for both the 1-norm distance, figure 2(a), and the information metric, 2(c). Here the spatial relationships of the red sensors have been found, with sensor $R1$ in the upper left corner and $R64$ in the lower left corner for the 1-norm distance and the $R1$ sensor in lower left corner for the information metric. Since the sensory reconstruction method cannot find the true physical location of sensors but only the spatial relationships both of these maps represent the visual field.

Up until now the term "reconstructed" has been used in an informal way, where a visual field is reconstructed if the sensoritopic map and the real layout of the sensors look similar. One way this similarity can be formally quantified is by computing the relative distances between pairs of sensors in the reconstructed visual field and the real layout of the sensors. Let $r_{i,j}$ be the Euclidean distance between two sensors i and j in the reconstructed map, and $\ell_{i,j}$ the distance between the same two sensors in the real layout, where the x and y coordinates in both cases have been normalised into the range $[0.0, 1.0]$. Now the average distance between all pairs of sensors can be compared,

$$d(r,\ell) = \frac{1}{N^2} \sum_{i,j} |r_{i,j} - \ell_{i,j}|, \qquad (10)$$

where N is the number of sensors. This compares the relative positions of the sensors and not the physical positions, and $d(r,\ell)$ will have a value in the range $[0.0, 1.0]$. A distance of zero means that the relative positions are exactly the same, and sensors placed at completely random positions will have an average distance of approximately 0.52.

Table 1 shows the average distances for 10 created maps for each of the five sets of data using equation 10. The 64R column shows that the 1-norm and information metric have a significantly lower average distance then the other measures, indicating that using these two measures more accurately reconstructs the real visual field.



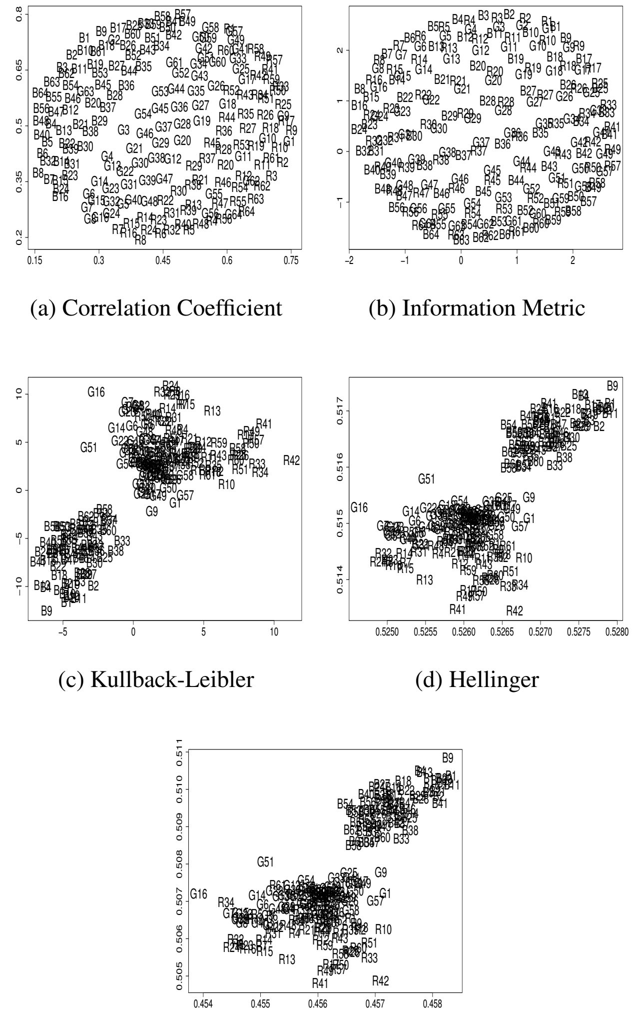
(a) 1-norm (b) Correlation Coefficient

(c) Information Metric (d) Kullback-Leibler

(e) Hellinger (f) Jensen-Shannon

Figure 3: Sensoriopic maps of 192 sensors using uniform binning.

Figure 3 shows sensoritopic maps for all the red, green, and blue sensors, and column 192RGB of table 1 show the corresponding average distances. This is an example of sensor integration where the problem is to find what sensors that are from the same location of the visual field, when the only input data to the system is the raw and unstructured data from the 192 sensors without any classification. The



(a) Correlation Coefficient (b) Information Metric

(c) Kullback-Leibler (d) Hellinger

(e) Jensen-Shannon

Figure 4: Sensoriopic maps of 192 sensors using entropy maximization of the sensor data.

Hellinger map and Jensen-Shannon map both contain three clusters, one for each modality. The Kullback-Leibler map is divided in to four clusters. The 1-norm distance shows how structure within the modalities is present but there is no fusion of the sensors from different modalities. The correlation coefficient measure shows a similar structure but there is some overlap between the red and the green sensors. For the information metric, figure 3(c), the situation is different. Here the sensors of different modalities from the same location in the visual field are clustered together. This is an example of autonomous sensory fusion where sensors of different modalities are combined. A well-studied example of this in neuroscience is the optic tectum of the rattlesnake, where nerves from heat-sensitive organs are combined with nerves from the eyes (Newman and Hartline, 1981).

In (Olsson et al., 2005c) it was shown how entropy maximization of the data in individual sensors might be useful to find correlations between sensors of different modalities. Figure 4 shows sensoritopic maps and column 192ARGB of table 1 the average distance computed using the same data as before where it has been preprocessed by maximizing the entropy in each sensor using a window of 100 time steps (see (Olsson et al., 2005c) for details of this method). The 1-norm distance is not included since it is operating on raw sensor values and not on probabilities. The Kullback-Leibler, Hellinger, and Jensen-Shannon measures now cluster the red and green together and the blue in another cluster. The map of the correlation coefficient is similar, albeit with with more structure showing the layout of the individual sensors of the different modalities, as also can be seen in the average distance in table 1. The information metric in figure 4(b) again shows clustering of the different modalities according to their spatial location in the visual field. For example is sensor *R*28 clustered together with *B*28 and *G*28.

Discussion

Why is it the case that the information metric enables the sensory reconstruction method to find these relations between sensors of different modalities when the other measures do not? By considering the individual as well as joint entropies of the sensors the information metric provides a general method for quantifying all functional relationships between sensors, while many other methods only find some relationships. For example, a correlation coefficient approaching 0 does not imply that two variables actually are independent (Steuer et al., 2002).

Conclusions

For purposes of autonomous construction of the relations among sensors in an embodied agent, in this paper we compared the information metric to five other distance measures: the 1-norm distance, the correlation coefficient, Kullback-Leibler divergence, Hellinger distance, and the Jensen-Shannon divergence. Among these the information metric, 1-norm distance, Hellinger distance, and the squared Jensen-Shannon divergence are metrics in the mathematical sense. The comparision was performed by applying the distance measures as the distance measure used in the sensory reconstruction method. The created sensoritopic maps were evaluated by comparing the average spatial distances of the sensors of the reconstructed maps with the spatial distances between the sensors of the real square layout of the sensors.

The results showed that for autonomous construction of the relationships between sensors of different modalties, sensoritopic reconstruction using the information metric was the only successful method, outperforming all the other distance measures. When using sensors from only one modality the average reconstruction distance of the information metric was similar to the 1-norm distance. Among the other proposed measures the correlation coefficient had a shorter average distance than the others, but still significantly greater than the information metric. This is due to the fact that the information metric captures general relationships between sensors and not just linear relationships, as is the case with many other measures.

In recent years there has been an increased interest in studying the informational relationships between robots, their environment, and how their actions affect the information available in their sensors. Here the information metric is useful since it captures general relationships between sensors. This has, for instance, been exploited to discover optical and information flow in sensors of different modalities (Olsson et al., 2005a, 2006), and to build "interpersonal maps" that represent the informational relationships between two agents (Hafner and Kaplan, 2005). It has also been used to study the informational content available to robots in environments with oriented contours (Olsson et al., 2004a), inspired by the developmental studies of kittens reared in restricted visual environments (Wiesel, 1982; Callaway, 1998).

One possible avenue for future research is to study how robots, just like animals, can optimize their sensory system based on the statistics of their specific environments, as well as the actions and embodiment of the particular robot. Here the construction of sensoritopic maps using the information metric can be used as a general method to find the informational relationships between the sensors and the actions of the robot. It would also be of interest to study how a robot actively can shape the informational relationships among its sensors by deliberate actions.

Acknowledgements

The work described in this paper was partially conducted within the EU Integrated Project RobotCub ("Robotic Open-architecture Technology for Cognition, Understanding, and Behaviours") and was funded by the European Commission through the E5 Unit (Cognition) of FP6-IST under Contract FP6-004370.

References

Barlow, H. B. (1961). Possible principles underlying the transformation of sensory messages. *Journal of Sensory Communication*, pages 217–234.

Basu, A., Harris, I. R., and Basu, S. (1997). Minimum distance estimation: The approach using density-based distances. In Maddala, G. S. and Rao, C. R., editors, *Handbook of Statistics*, volume 15, pages 21–48.

Callaway, E. M. (1998). Visual scenes and cortical neurons: What you see is what you get. *Proceedings of the National Academy of Sciences*, 95(7):3344–3345.

Cover, T. M. and Thomas, J. A. (1991). *Elements of Information Theory*. John Wiley & Sons, Inc.

Crutchfield, J. P. (1990). Information and its Metric. In Lam, L. and Morris, H. C., editors, *Nonlinear Structures in Physical Systems – Pattern Formation, Chaos and Waves*, pages 119–130. Springer Verlag.

Endres, D. M. and Schindelin, J. E. (2003). A new metric for probability distributions. *IEEE Transactions on Information theory*, 49(7):1858–1860.

Ernst, J., Nau, G. J., and Bar-Joseph, Z. (2005). Clustering short time series gene expression data. In *Proceedings of ISMB*. to appear.

Hafner, V. and Kaplan, F. (2005). Interpersonal maps and the body correspondance problem. In Demiris, Y., Dautenhahn, K., and Nehaniv, C. L., editors, *Proceedings of the AISB 2005 Third International Symposium on Imitation in Animals and Artifacts*, pages 48–53.

Kaplan, F. and Hafner, V. (2005). Mapping the space of skills: An approach for comparing embodied sensorimotor organizations. In *Proceedings of the 4th IEEE International Conference on Development and Learning (ICDL-05)*, pages 129–134.

Lin, J. (1991). Divergence measures based on the Shannon entropy. *IEEE Transactions on Information Theory*, 37(1):145–151.

Lungarella, M., Pegors, T., Bulwinkle, D., and Sporns, O. (2005). Methods for quantifying the informational structure of sensory and motor data. *Neuroinformatics*, 3(3):243–262.

Lungarella, M. and Pfeifer, R. (2001). Robots as cognitive tools: Information-theoretic analysis of sensory-motor sata. In *Proceedings of the 2nd International Conference on Humanoid Robotics*, pages 245–252.

Mirza, N. A., Nehaniv, C. L., te Boekhorst, R., and Dautenhahn, K. (2005a). Robot self-characterisation of experience using trajectories in sensory-motor phase space. In *Proceedings of the fifth international workshop Epigenetic Robotics*, pages 143–144.

Mirza, N. A., Nehaniv, C. L., te Boekhorst, R., and Dautenhahn, K. (2005b). Using sensory-motor phase-plots to characterise robot-environment interactions. In *Proceedings of the 6th IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA-2005)*, pages 581–586.

Newman, E. A. and Hartline, P. H. (1981). Integration of visual and infrared information in bimodal neurons of the rattlesnake optic tectum. *Science*, 213:789–791.

Olsson, L., Nehaniv, C. L., and Polani, D. (2004a). The effects on visual information in a robot in environments with oriented contours. In *Proceedings of the Fourth International Workshop on Epigenetic Robotics*, pages 83–88. Lund University Cognitive Studies.

Olsson, L., Nehaniv, C. L., and Polani, D. (2004b). Sensory channel grouping and structure from uninterpreted sensor data. In *Proceedings of the 2004 NASA/DoD Conference on Evolvable Hardware*, pages 153–160. IEEE Computer Society Press.

Olsson, L., Nehaniv, C. L., and Polani, D. (2005a). Discovering motion flow by temporal-informational correlations in sensors. In *Proceedings of the Fifth International Workshop on Epigenetic Robotics*, pages 117–120. Lund University Cognitive Studies.

Olsson, L., Nehaniv, C. L., and Polani, D. (2005b). From unknown sensors and actuators to visually guided movement. In *Proceedings of the Fourth International Conference on Development and Learning (ICDL 2005)*, pages 1–6. IEEE Computer Society Press.

Olsson, L., Nehaniv, C. L., and Polani, D. (2005c). Sensor adaptation and development in robots by entropy maximization of sensory data. In *Proceedings of the Sixth IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA-2005)*, pages 587–592. IEEE Computer Society Press.

Olsson, L., Nehaniv, C. L., and Polani, D. (2006). From unknown sensors and actuators to actions grounded in sensorimotor perceptions. *Connection Science*, 18(2).

Pierce, D. and Kuipers, B. (1997). Map learning with uninterpreted sensors and effectors. *Artificial Intelligence*, 92:169–229.

Prince, C., Helder, N. A., and Hollich, G. J. (2005). Ongoing emergence: A core concept in epigenetic robotics. In *Proceedings of the fifth international workshop Epigenetic Robotics*, pages 63–70.

Sporns, O. and Pegors, T. K. (2003). Generating structure in sensory data through coordinated motor activity. *Proceedings of the International conference Neural Networks*, page 2796.

Sporns, O. and Pegors, T. K. (2004). Information-theoretic aspects of embodied artificial intelligence. *Embodied Artificial Intelligence, LNCS 3139*, pages 74–85.

Steuer, R., Kurths, J., Daub, C. O., J., W., and Selbig, J. (2002). The mutual information: Detecting and evaluating dependencies between variables. *Bioinformatics*, 18:231–240.

Tarapore, G., Lungarella, M., and Gómez, G. (2004). Fingerprinting agent-environment interaction via information theory. In Groen, F., Amato, N., Bonarini, A., Yoshida, E., and Kröse, B., editors, *Proceedings of the 8th International Conference on Intelligent Autonomous Systems, Amsterdam, The Netherlands*, pages 512–520.

Wiesel, T. (1982). Postnatal development of the visual cortex and the influence of environment. *Nature*, 299:583–591.